Degree of Master of International Studies

VARIABLE INTERNAL COHESION AND EPISTEMIC COMMUNITY INFLUENCE: THE ARCTIC CLIMATE IMPACT ASSESSMENT REPORT

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International Cooperation Program
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VARIABLE INTERNAL COHESION AND EPISTEMIC COMMUNITY INFLUENCE:

THE ARCTIC CLIMATE IMPACT ASSESSMENT REPORT

A thesis presented

by

GAUTE FRIIS

A dissertation submitted in partial fulfilment
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July 2017

Candidate for the degree of Master of International Studies

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Thesis Title: Variable Internal Cohesion and Epistemic Community Influence:
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Abstract

This analysis seeks to test an emerging theory of epistemic community influence. The theory posits that higher internal cohesion amongst members of an epistemic community will garner the community more political influence (Cross 2013).

Taking advantage of a large citation database, as well as other open source datasets, this thesis produces a complex, undirected, weighted, multilevel (tripartite), temporal, spatially distributed graph of global scientific collaboration in Arctic research.

Using concepts developed in the Social Network Analysis (SNA) literature, this thesis operationalizes cohesion, and seeks to test its effect on one specific case of an epistemic community: the group of researchers who collaborated on the influential Arctic Climate Impact Assessment report (ACIA 2005).

The results contests the original hypothesis and opens for a more complex understanding of the effect of internal cohesion on an epistemic community's political influence.

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I Purpose and Background

1 Science and diplomacy

It has become a truism that globalization and increasing interdependence are creating a world of growing complexity and uncertainty that is eroding the classic patterns of international relations (Smith 2008). The increasing complexity of world problems means evidence-based policies are more important than ever (Haas 2016b, p. 47). But what are the casual pathways in which expert knowledge reaches and informs political decision-making?

The Epistemic Community (Epicom) literature is the principal way in which these processes have been examined within International Relations (IR) theory. For the last 25 years, studies of epistemic communities have examined how various expert groups have been able to influence political decisions on the highest level.

Nowhere is this state of affairs more present than in the Arctic. Due to its extreme weather conditions, operating in the Arctic generally requires specialized knowledge and equipment. Experts and scientists have therefore had a large role the development of the Arctic governance structure. Examples are the Joint Norwegian–Russian Fisheries Commission (Hønneland 2000), the Arctic Search and Rescue Agreement (Farré, A. B., et al. 2014), the Commission on the Limits of the Continental Shelf (Baker 2010), and the various Arctic Council working groups (Arctic Council 2013).

However, studies in the epistemic community literature has primarily been single case studies, or smaller comparative research. Large empirical and statistical tests are quite rare (Haas 2016). While this thesis is also a case study, and rather exploratory in nature, its introduction of a new methodological paradigm opens the doors for large-scale, quantitative, inferential studies on epistemic communities.

2 *Methodological development*

The epistemic community literature is part of the constructivist branch of international relations theory. Unlike the state-centric approaches embodied by the realist branches, epicom theory argues that “states make choices subject to multiple sources of influence, whose organization varies by influence area. Thus, governance varies by issue area. Consequently *policy networks*, organized around specific issues become the appropriate level and unit of analysis because the array of actors, interests, institutions, and capabilities varies by issue.” (Haas 2016, emphasis mine).

Conceiving of political processes as happening through policy networks has a long tradition in political science (Rhodes 2006). However, this approach often discusses networks more like a metaphor rather than a precise model, something that may lead to a vagueness and imprecision that makes it hard to generalize theories and conduct large-N comparative research, a longstanding criticism of the approach (Dowding 1995).

The burgeoning field of Social Network Analysis (SNA) on the other hand, is of a rather quantitative nature, and often demand a high level of definitional precision when developing concepts. It also allows for the empirical study of large, complex networks that would not be feasible using alternative approaches. Furthermore, it allows the researchers to take advantage of the concepts and mathematics developed in graph theory. In the case of the present study, the concept in question is that of cohesion amongst the members of an epistemic community.

Prior applications of SNA to the study of epicoms have been primarily interested in community detection (Roth, Obiedkov & Kourie 2008). As far as I can tell, the present study represents the first time SNA concepts have been applied to the measure of the political influence of an epistemic community.

The goal of this thesis is therefore twofold; mainly it is an attempt to empirically test an emerging theory on epistemic community influence. Additionally, it seeks to highlight the usability and potential of social network analysis in the epistemic community literature.

II Research Question and Case Selection

1 *Research question*

In her review article of two decades of epistemic community research, Cross (2013, p. 144) summarizes several proposed conditions under which epicoms might be influential. She also proposes her own structural theory: "*I hypothesise that the more internally cohesive an epistemic community, the more likely it will achieve a high degree of influence on policy outcomes.*"

This theory will attempt to operationalize and test her theory on variable internal cohesion and epistemic community influence. It will do so using the social network analysis framework, and in particular a measure called "clustering coefficient" as well as various centrality measures which will all be explained in-depth below. It will do so by creating a network of the entire global research community on Arctic research, and in particularly by looking at a group of scientists involved in a large report on climate change in the Arctic named the Arctic Climate Impact Assessment Report (ACIA 2005).

The research question is "*is the cohesion, as measured by the clustering coefficient of their collaboration pattern, of the ACIA epistemic community higher than that of the general research network?"*

I hypothesize that, as Cross (2013) suggests, this influential group of scientist ought to have a high level of cohesion, and exhibit a strong, dense network.

2 Case selection: The Arctic Climate Impact Assessment Report

The author wishes to stress that this study, unlike many others in the discipline, does not seek to determine whether an epistemic community *was* influential, but whether an influential community was cohesive or not. It therefore starts with a community whose impact and influence are relatively undisputed, namely the group authoring the 2005 Arctic Climate Impact Assessment Report.

The Arctic Climate Impact Assessment Report (ACIA 2005) was the first international regional climate impact assessment. It was created under the auspices of the intergovernmental Arctic Council (AC) and the non-governmental International Arctic Science Committee (IASC).

The 1042-page scientific report was co-authored by 309 individuals, most of whom were scientists. It is these scientists that form the epistemic community that is the focal case study of this thesis. Unlike the more famous reports released by the Intergovernmental Panel on Climate Change (IPCC), the ACIA report was notable for including many social scientists as well as representatives of indigenous groups (Nilsson 2009).

This "seminal" (Lemke & Jacobi 2011, p. 455) report is generally regarded as a highly influential and its results garnered major attention in the media when they became public in 2004. Comparing the public reception of with the third IPCC report (Houghton, et al. 2001), Tjernshaugen & Bang (2005) concluded that "*we find that the IPCC report received more attention that ACIA. But given the much broader thematic scope of the IPCC assessment, it is reasonable to conclude that even in comparison to the IPCC report ACIA has received a large amount of attention.*" Going on to note: "*We also find that so far there have been markedly fewer references to disagreement over the scientific content and form of presentation of the ACIA report."*

That the ACIA report was generally accepted and influential is widely agreed upon in the political science literature discussing the report. (Duyck 2012, Stokke & Hønneland

2006, Stone 2015, Young 2016, Soltvedt & Rottem 2016, Koivurova & Hasanat 2009, Nilsson 2009).

One of the most notable results of the report from a policy perspective was that the Senior Arctic Officials (SAOs) of the Arctic Council formulated a document with concrete policy recommendations that was derived from the findings in the ACIA report. (Arctic Council 2004a, Arctic Council 2004b). The policy document appealed the member states of the Arctic Council to "*adopt climate change mitigation strategies [in order to reduce greenhouse gases to] levels consistent [with] the ultimate objective of the UNFCCC*" (United Nations Framework Convention on Climate Change), thus, "*representing the strongest call for climate mitigation policies endorsed by the Arctic Council*" (Nilsson 2007, p. 131-142). Few studies have analysed the extent of the national implementation of these policy recommendations, but the one this author is aware of (Soltvedt & Rottem 2016) shows that, at least in the case of Norway, several, though certainly not all, of the recommendations has in fact been implemented into domestic law.

As noted by Duyck (2012, p. 609) "*While such statements seldom result in concrete outcomes, they might be relevant to climate change negotiations in influencing the rhetoric used*". Koivurova & Hasanat (2009) notes that the ACIA report were produced in the "*context of a lack of strong political commitment by the eight Arctic states*". (Duyck 2012, p. 614). Despite of this, they highlight the political power it had in framing the climate change debate: "*A good argument can be made that the [ACIA process] has been able [...] to influence even the global climate change regime since it is fairly uncontested that the increase and progress in knowledge of climate change and its consequences puts pressure on the politico-legal machinery to strengthen the climate regime*." (Koivurova & Hasanat 2009). Oran Young likewise argues that the ACIA report "*strengthened the foundations of the global climate negotiations*" (2016).

Outside of academia, the importance of the work conducted by the ACIA epistemic community has also been highlighted by politicians active in Arctic governance, as seen when then Norwegian Minister of the Environment, Bård Vegar Solhjell stated "*[ACIA] provided the basis for decisions on several international conventions and agreements in which the main point is to get control of emissions of pollutants that eventually end up in the Arctic ecosystems.*" (Arctic Council 2012).

That the ACIA report came at a critical juncture can be seen by tracking how often the terms "climate change" and "global warming" have been mentioned in publications as well. Google Ngram, which queries the Google Books database for mentions of certain keywords, can do just that. As Figure 1 shows, 2004, when the 140-page synthesis report *Impacts of a Warming Arctic* (ACIA 2004) was released, if was a key part of a major uptick in the global focus on climate change that started with the third IPCC report (Houghton, et al.) in 2001 and was further catapulted into the global conscious by Al Gore's documentary film An Inconvenient Truth in 2006 (Guggenheim).

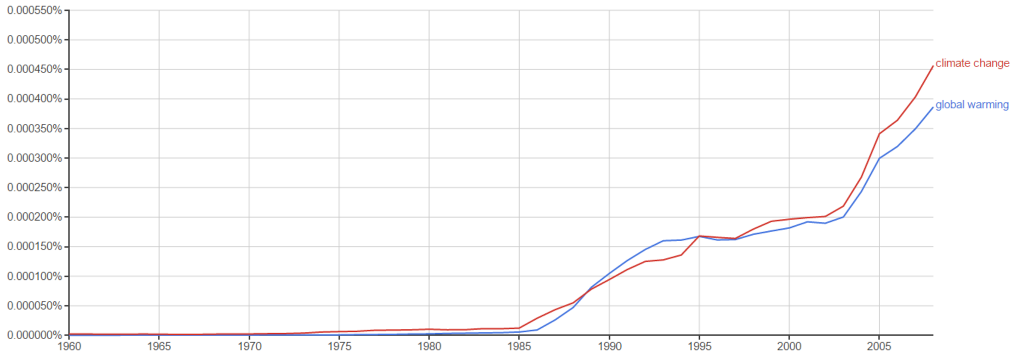

Figure 1. Google Books Ngram viewer charting the rise of the terms "climate change" and "global warming". © John Cook at the Center for Climate Change Communication at George Mason University.

III Literature Review

1 Epistemic communities

Peter Haas, the founding father of the epistemic communities literature defines them as *"networks of knowledge-based communities with an authoritative claim to policy-relevant knowledge within their domains of expertise. [...] they are a group of professionals, often from a number of different disciplines, who share the following characteristics:*

1. *Shared principled beliefs. Such beliefs provide a value-based rationale for social action by the members of the community.*
2. *Shared causal beliefs or professional judgment. Such beliefs provide analytic reasons and explanations of behavior, offering causal explanations for the multiple linkages among possible policy actions and desired outcomes.*
3. *Common notions of validity: intersubjective, internally defined criteria for validating knowledge. These allow community members to differentiate confidently between warranted and unwarranted claims about states of the world, and policies to change those states.*
4. *A common policy enterprise: a set of practices associated with a central set of problems that have to be tackled, presumably out of a conviction that human welfare will be enhanced as a consequence"* (Haas 2016, p. 5)

Each of the four characteristics are required for the group to warrant the designation as an epistemic community. The ACIA researchers fit these criteria well, as they co-authored a major document that contains elements of each criteria. The report (ACIA 2005) argues that the Earth represents an ecosystem with finite resources that must be harvested in a sustainable manner (a principled belief), that anthropogenic greenhouse gases are causing a global warming (a causal belief), that there is mounting evidence of this process which can be found through the scientific method (a *notion of validity),* and the report even comes with a policy paper prescribing a number of mitigation and adaptation measures (a policy enterprise).

Again, since they all signed off as co-authors, one must assume that they agree with each other's findings and methodologies, and that they thus constitute an epistemic community.

1-1 Epistemic Community Influence and Variable Internal Cohesion

After its emergence as a major theory of International Relations in a special issue of *International Organization* in 1992, the concept of epistemic communities has seen a sizeable literature spring up to examine its applicability in a range of cases. This literature has recently seen summaries in an article by Mai'a Cross (2013), and more recently in a book-length collection of articles by Peter Haas himself (2016).

While Haas' monograph is largely a historical overview of his own considerable contributions, Cross seeks to expand the research programme in new directions, or to "*put forward specific innovations to the framework*" as she says herself (2013, p.138). Specifically, she argues that "*we must pay more attention to the internal dynamics within an epistemic community to understand its strength or weakness*" (2013, p.138).

After introducing a helpful table (reworked from Zito [2001]) showcasing under what circumstances studies have shown epistemic communities to successfully influenced global politics, she advances one major new hypothesis dealing with the internal structure of an epistemic community, namely that of *variable internal cohesion*.

Epistemic communities are more likely to be persuasive When:	Scholars:
Scope conditions	
there is uncertainty surrounding the issue because it is complex or new (uncertainty from perceived crisis)	Haas (1990), Radaelli (1999)
the issue is surrounded by uncertainty and it is politically salient (continuous uncertainty)	Radaelli (1999)
the decision-makers they are trying to persuade are unhappy with past policies and present problems (uncertainty from perceived crisis)	Hall (1993)
Political opportunity structure	
they have access to all necessary top decision-makers	Haas (1990), Drake and Nicolaïdis (1992)
they anticipate other actors' preferences and actions despite fluidity in the system (as in the EU)	Richardson (1996)
Phase in the policy process	
they seek to influence the terms of the initial debate, instead of the decision itself	Raustiala (1997)
they deal with subsystem, technocratic phase of decisionmaking, rather than shaping broader political beliefs	Peterson and Bomberg (1999)
Coalition building	
the networks they are competing against are not as cohesive or certain of their aims	Peterson (1995)

they share a high level of professional norms and status	Sabatier and Jenkins-Smith (1999)
Policy field coherence there is respected quantitative data, instead of very subjective qualitative data	Sabatier and Jenkins-Smith (1999)
the issue involves natural systems (that is, the environment), instead of social systems	Sabatier and Jenkins-Smith (1999)
their norms and policy goals are compatible with existing institutional norms	Jordan and Greenway (1998), Sabatier (1998)

Table 1. When epistemic communities are persuasive: summary of the literature

Cross argues that much of the literature summarized in Table 1 looks mainly to the external conditions and overarching comparative political context that constrains or enables the epistemic community to exercise influence. After taking account of these external conditions, she argues, "*the next step is to look at an epistemic community's internal dynamics*." In this respect, "*a major hypothesis I put forward is that a strong epistemic community that has a greater potential for influence is one that not only possesses a high degree of recognised expertise, but is also internally cohesive.*" (2013, p. 148).

It is this idea of "cohesion" that the present study wish to operationalize, and to furthermore test whether a known influential epistemic community really does exhibit higher levels of cohesion.

2 Graph Theory:

Graph theory is the branch of mathematics that deals with the relationships between points and lines. These are called “vertices” and “edges” respectively, although the more intuitive “nodes” and “links” are often used in social sciences (which will also be the case in the present study). In Figure 2, the numbered circles are the vertices/nodes, and the lines between them are the edges/links. The circles and lines can represent anything, but in this study the circles will generally represent researchers, while the lines will represent coauthorship on one or more publications. In the context of social science, a graph is often called a sociogram.

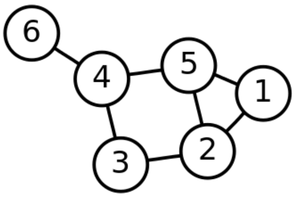

Figure 2. A simple graph. © AzaToth, Used under Creative Commons Attribution 2.0 Generic

Graph theory provides both a visual representation of a network (the sociogram) and a collection of measures and concepts that can be utilized to study the formal properties of social networks (Wasserman & Faust 1997, p. 15). This gives us a standardized language for talking about and quantifying structure and properties of the networks, avoiding the pitfalls mentioned in chapter I2 (Hoffman 2011).

3 Social Network Analysis (SNA):

SNA is the social science brother of graph theory. It seeks to find applications to help us better understand social phenomena around us. Some authors like to draw a distinction between what they call relational science and attribute science (Scott 2012).

Attribute science represents the "traditional" way of ordering the world where individual observations are given certain attributes (like gender, socioeconomic status), and are then investigated using statistical analysis (Scott 2012).

Relational science on the other hand, represent an alternative approach. Here you are no longer seeing observations as independent individuals, but rather as embedded in a web of social relations. It is no longer the attributes of an individual observation per se that is interesting, but his position in this web, and how it is navigated.

Take for example the financial portfolio of a hedge fund where each individual asset has a risk associated with it. If these assets are not related in anyway, because they all stem from separate sectors of the economy, then simply analysing the risk attributes of each asset and adding them together in a linear way is a reasonable way to find a total value for the whole portfolio.

But what if the case is that many of the assets in the portfolio are interconnected and dependent on each other? A large number of investments in logistics and retail, or agriculture and food processing, for example, will see the risk grow in unpredictable, nonlinear ways (Colchester 2017). As failure in one set of assets will result in the diffusion of failure (and thus increased risk) across a broad range of assets.

Therefore, the actual risk-return ratio of the complete portfolio cannot reasonably be calculated by analysing each asset in isolation, but must take account of these complex interconnections (Colchester 2017).

Once a system sees increasing connectivity (such as the global governance system), it is increasingly the relations between individual components that tends to determine the outcome of changes in the overall system (Bar-Yam 1997). This is where the toolset afforded by network theory really shines, as it allows us to grapple directly with this increasing complexity by its ability to handle large datasets, and allows us to be very precise when formulating and testing various hypotheses.

The formal definitions of a number of network/graph theory concepts and clustering algorithms are introduced in Chapter IV.

IV Methodology

1 Research design

The research process will go through the five stages outlines in Figure 3. These steps will be detailed in this chapter and the next.

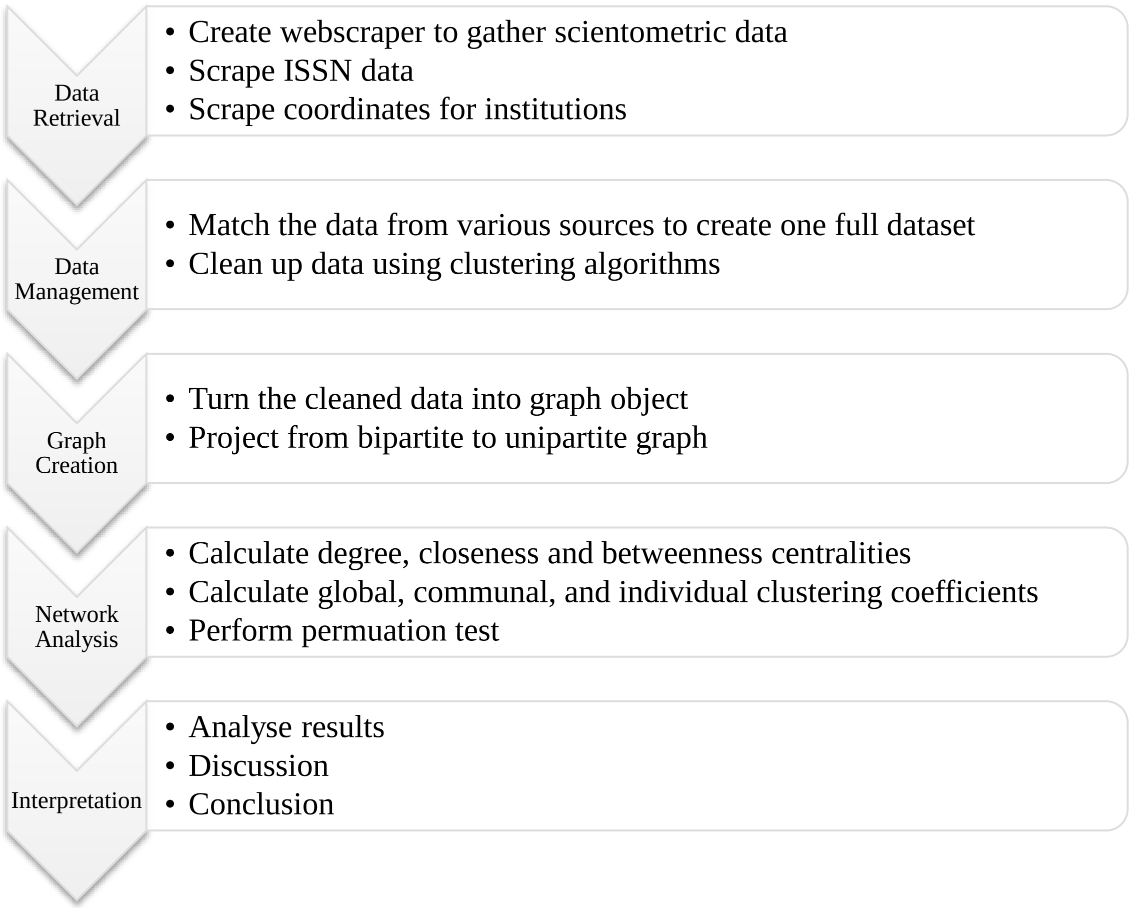

Figure 3. Research process

2 Data retrieval

In order to map the global arctic research network that the ACIA researchers are embedded in, it is necessary to find a suitable dataset. Since the epistemic community in question consists of more than 300 members, performing qualitative data gathering like surveys, interviews, or “snowballing” are out of the question (Scott 2012, p. 49-50).

Rather, I will take advantage of a large citation database in order to capture collaboration patterns amongst the scientist. By accessing databases like Google Scholar or Web of Science and retrieving metadata on every relevant paper available in the database, one could create an algorithm that defines every author as a node, and every time two or more authors have co-authored a paper, it creates a link between them. By doing this on every paper downloaded, one would eventually create a graph of the entire research network.

The database I chose to utilize was Elsevier’s Scopus. According to the website, Scopus contains “more than 66 million records” found in “over 22,748 peer-reviewed journals.” in addition to a large amount of conference papers and books (Elsevier 2017). In addition to its comprehensive scope, Scopus was chosen for its friendliness to web scraping algorithms. Automatic data retrieval is severely curtailed in Google Scholar and requires paid subscription in Web of Science.

A webscraping bot was built to interact with Scopus’ Application Program Interface (API), an interface for data retrieval. The algorithm were set to download the metadata on all papers containing the word 'arctic' in their title, keywords, or abstract, every year back to 1945.

The data were retrieved on Jun 25, 2016. 50,189 papers written by 78,901 authors belonging to 17,576 institutions were collected. This led to a combined 146,666 observations in the raw data.

Furthermore, separate algorithms were built to scrape another of Elsevier's databases containing information on the impact factor of various journals, as well as to retrieve the coordinates for the institutions, so they could be geographically displayed and spatially analysed. This latter data was gathered from the free and open source Geonames database (Wick, M., & Vatant, B. 2012).

3 Data management

Unfortunately, with such a large number of observations in the dataset, an equally large number of errors were to be found. Particularly did this relate to the various institutions (the observations relating to authors and journal articles had a much higher data integrity). Table 2 is an example of such messy data. What seems to be only *one* research institute would instead have become ten (!) different nodes in the network, severely undermining the reliability of the resulting network graph.

Table 2. Example of messy data

ID number	Name
105221434	Nansen International Environmental and Remote Sensing Center
101437938	Nansen Intnl. Envrn./Remote Sensing
60104160	Nansen International Environmental and Remote Sensing Centre
116553585	Nansen Environmental and Remote Sensing Centre (NERSC
100368444	Nansen Intl. Environ. Remote S.
60026154	Nansen Environmental and Remote Sensing Center
112795981	Scientific Foundation Nansen International Environmental and Remote Sensing Center
100468722	Nansen International Environmental and Remote Sensing Center
100660746	Nansen Environmental and Remote
100328539	Nansen Int Environmental and Remote

While this one instance is simple enough to rectify manually, with more than 17,000 institutions in the database, checking each and every one manually is simply not feasible. This problem is typical of the kind of challenges one faces when trying to use “big data,” and thankfully there are a number of clustering methods and algorithms invented for cases such as these. The following will list them in order from most strict to most lax, with a short description of their workings.

3-1 Clustering methods and algorithms

The clustering techniques applied can be separated into two broad categories, the so called "Key Collision" methods, and the “Nearest Neighbour” methods.”

"Key Collision" methods attempts to find the simplest, most meaningful way of signifying a value (a "key"), and then seeing if other entries in the database have the same key.

3-1-1 Fingerprint

The fingerprinting method, first implemented by Rabin (1981), is one of the simplest clustering algorithms to understand. It attempts to generate a key from a value by following these steps (from Stephens 2016):

1. Remove leading and trailing whitespace
2. Change all characters to their lowercase representation
3. Remove all punctuation and control characters
4. Split the string into whitespace-separated tokens
5. Sort the tokens and remove duplicates
6. Join the tokens back together

7. Normalize extended western characters to their ASCII representation (for example "gödel" → "godel")

By removing all the "dirt" from the value string, only the most meaningful part of the string remains, and the same ones are clustered together (or their "keys collide", hence the name). The order of the tokens is not important, so "Kurt Godel" and "Gödel, Kurt" will end up in the same cluster.

3-1-2 N-Gram Fingerprint

The n-gram fingerprint method, in this instance as developed by Cavnar & Trenkle (1994), largely follows the steps of the fingerprinting algorithm, except that instead of using whitespace-separated tokens, it uses so-called "n-grams." N-grams allows the user to choose the length of a sequence of letters in the token that may be dissimilar but yet end up in the same cluster. This means that names like "Krzysztof", "Kryzysztof" and "Krzystof" can be found together, even though they have different fingerprints.

3-1-3 Metaphone3

Metaphone3, developed by Philips (1990) is a so-called "Phonetic Fingerprint" algorithm. It creates the key by transforming words into the way they are pronounced.

"Reuben Gevorkiantz" and "Ruben Gevorkyants" have end up with different keys using both the n-gram and basic fingerprinting (Stephens 2016), however, their pronunciation is the same and they will thus be clustered using Metaphone3.

Nearest neighbour methods are computationally more demanding than key collision methods, but they allow the user more precision when searching for duplicates. The user is free to choose how “far apart” any strings are allowed to be without being clustered together.

3-1-4 Levenshtein Distance

Developed by Levenshtein (1966), this algorithm counts the amount of changes that are needed to make one string identical to anoter. To use an example from Stephens again (2016): “*’Paris’ and ‘paris’ have an edit distance of 1 as changing P into p is the only operation required. ‘New York’ and ‘newyork’ has edit distance 3: 2 substitutions and 1 removal. ‘Al Pacino’ and ‘Albert Pacino’ have an edit distance of 4 because it requires 4 insertions.”*

This makes Levenshtein distance particularly useful for finding spelling errors or similar things that slipped by during the previous methods.

3-1-5 Prediction by Partial Matching

Prediction by Partial Matching, or PPM, is based on the idea of using the information-theoretical notion of “Kolmogorov complexity” to measure the correspondence between two values or strings.

Kolmogorov complexity is measured by how small the simplest computer program needed to generate a given output is. The smaller the program, the less complex the output.

PPM is a compressor algorithm that takes a string and tries to reduce in size, and it does this statistically estimating what character will come after another. So if string X and Y are similar, compressing X or compressing X+Y should end with similar results (measured by Kolmogorov complexity). If X and Y were very different, compressing them would lead to a very different result than when compressing X by itself.

The result is that, while PPM yields many false positives, it also has the ability to uncover some deep connections that are very hard to spot otherwise (Stephens 2016).

These algorithms were all implemented in OpenRefine, an open source application for data wrangling (OpenRefine 2017).

However, since these algorithms work automatically they can often create problems on their own. If we look back at Table 2. Example of messy data and examine it in more detail, we find that it is in fact not one, but two related research centres. One is the Nansen Environmental and Remote Sensing Center located in Bergen, Norway, and the other one is the Nansen *International* Environmental and Remote Sensing Center, located in St. Petersburg, Russia. In order to mitigate risks like this, all merges suggested by the various algorithms were manually approved by the author. After the process of cleaning the data, the number of institutions in the dataset went from 17,576 to 16,513

4 Graph creation

With the dataset cleaned up one are now in a position to actually create the graph. This is done by creating another algorithm to go through the data and start defining relationships between the entities within. There are three kinds of entities in the dataset that are of value to the present study:

1. The scientists themselves

2. The institutions to which they belong

3. The papers they have written

The algorithm creates links where appropriate: when two or more scientists publish a paper together, a link is created between them. When a scientist belong to one or more institutions, a link is created between her and it/them. The end result is a complex, multilevel (tripartite), undirected, weighted, temporal, spatially distributed graph of global scientific collaboration on arctic research.

What does this mean?

- Multilevel (tripartite): means that the various kinds of nodes in the network (scientists, papers, institutions) exist on separate layers, and links within each layer is non-existent. E.g.: papers are not linked to other papers, and institutions are not linked to other institutions (only indirectly through a scientists). See Figure 4 for a visual representation of this structure.
- Undirected: links between node can be directional. This makes sense in for example a trade network, where one country might export to another, without necessarily importing anything from said country. However, it makes sense to assume that when two scientists are co-authoring a paper, they are both collaborating with each other.
- Weighted: weight refers to the frequency in which a link is used. If two authors write 1 paper together, their link gets a weight score of 1. If they write 2

papers, their score is 2 and so on. This captures that frequency of collaboration is likely a sign of a stronger relationship.

- Temporal: because all the paper-nodes have a publication date associated with them, it is possible to study the evolution of the network over time. When the graph is visualized, one can literally see collaborative patterns form and fade away.
- Spatially distributed: as mentioned earlier in this chapter, longitude and latitude where scraped from a geodatabase and associated with the various institutions. This allows the researcher to examine the geographical distribution of the network.

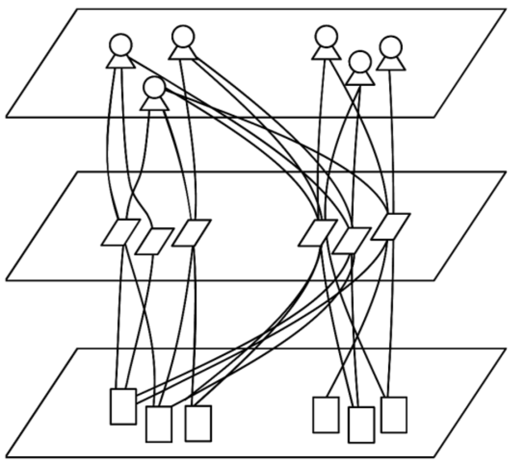

Figure 4. Illustration of a tripartite graph. © Kyohei Ikematsu and Tsuyoshi Murata, Tokyo Institute of Technology

5 *Social Network Analysis (SNA)*

With the network fully constructed, the researcher is finally able to take advantage of some of the unique opportunities to study structure that is afforded by the relational perspective of SNA.

5-1 Network measures

One of the key strengths of applying a SNA framework is the ability to formalize and test a number of concepts that are normally used only as metaphors or heuristics, such as “cohesion” and “network influence”. Take “centrality” for example, it is easy to claim that someone is a “central actor” in a certain context, but what do we really mean by that? Consider the graph in Figure 5**Feil! Fant ikke referansekilden.**, who is the central actor in this network?

Network analysist and graph theorists have thought about these questions for decades, and have come up with precise definitions of various conceptions of the idea of “centrality”. The following sub-chapters will introduce three of the most commonly accepted conceptions, which are also the ones who will be used later in this study.

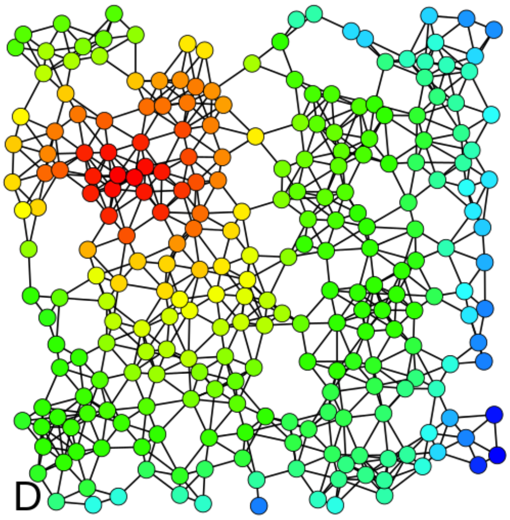

Figure 5. Centrality. Image by Tapiocozzo, licensed under CC BY-SA 4.0

5-1-1 Degree Centrality

Degree centrality is perhaps the most intuitive. It argues that the most central actors are those who have the most links. Figure 6 is the exact same network as in Figure 5, with only the colours having changed. For the rest of the chapter, a warmer colour equals a higher centrality score. In this case, red means that “the number of links incident upon a node” is high. It can therefore be understood as popularity, or in a co-authorship network, it would be particularly productive researchers who writes articles with a great many different people.

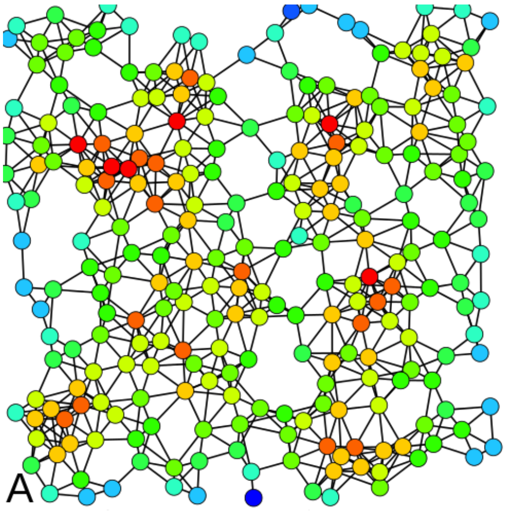

Figure 6. Degree centrality. Image by Tapiocozzo, licensed under CC BY-SA 4.0

Degree centrality can be formalized mathematically as in Equation 1, where the centrality of node v equals the number of nodes incident upon (degree) of node v.

Equation 1. Degree centrality

$$C_D(v) = \deg(v)$$

5-1-2 Closeness Centrality

When looking at Figure 6, none of the highly ranked nodes (the red ones) seems to be near the *central* part of the network. Closeness centrality seeks to remedy this, and ranks the nodes according to their distance to every other node. The definition is "the average length of the shortest path between the node and all other nodes in the graph" (Wasserman & Faust 1994, p. 184). The nodes with the highest centrality here are those who, on average, have the shortest path to every other node.

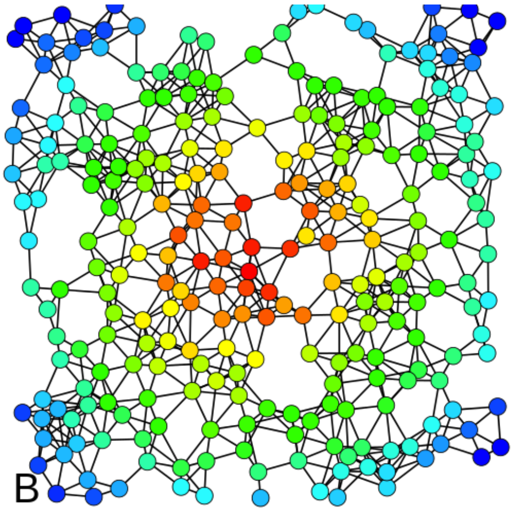

Figure 7. Closeness centrality. Image by Tapiocozzo, licensed under CC BY-SA 4.0

The mathematical formula is presented in Equation 2, where $d(y, x)$ is the distance from node y and x. (Bavelas 1950).

Equation 2. Closeness centrality

$$C(x) = \frac{1}{\sum_y d(y, x)}$$

5-1-3 Betweenness Centrality

Betweenness centrality is quite interesting. It starts with the shortest paths calculated in the previous algorithm, and then calculates which nodes sits on most of these paths. Formally, the definition is “the number of times a node acts as a bridge along the shortest path between two other nodes” (Brandes 2001). It is formalized as in Equation 3, where σ_{st} is total number of shortest paths from node s to node t and $\sigma_{st}(v)$ is the number of those paths that pass through v.

Equation 3. Betweenness centrality

$$C_B(v) = \sum_{s \neq v \neq t \in V} \frac{\sigma_{st}(v)}{\sigma_{st}}$$

While the other two forms of centrality stressed popularity and access, betweenness centrality can be better understood as someone being in a brokerage position, or acts as a bridge builder across communities/cohesive sub-groups.

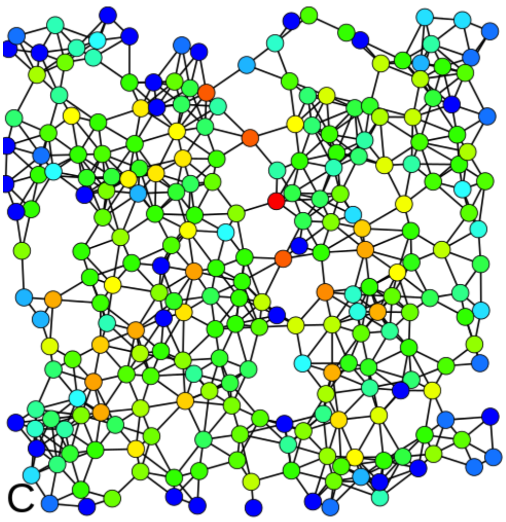

Figure 8, Betweeness centrality. Image by Tapiocozzo, licensed under CC BY-SA 4.0

5-1-4 Clustering Coefficient (CC)

Differing from the various centrality measures that seek to define and determine the influence of a given node, the measure called clustering coefficient seeks to determine the cohesiveness of its neighbourhood. Its starting point is the insight that “your friend is often my friend,” and the three friends will thus form a triangle. Extrapolating from this, one can measure the cohesiveness of a group by counting the number of triangles existing in a neighbourhood, divided by the number of all possible triangles.

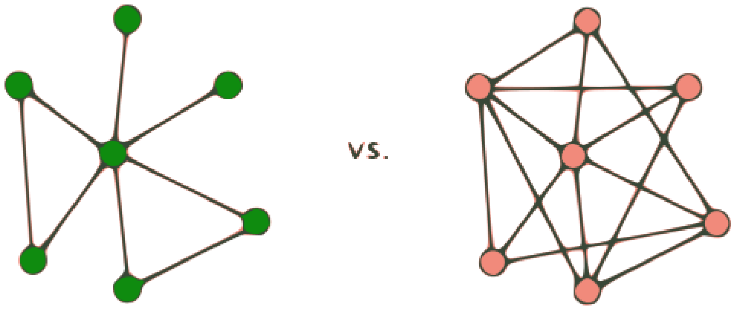

Figure 9. Example illustrating the clustering coefficient © Sergei Vassilvitskii, Yahoo! Research.

Consider the example in Figure 9. In the small network on the left, the middle green node has six connections. If everyone in this group were connected to everyone else, you would have 15 triangles. However, only 2 of the possible triangles exist, giving the green middle node a clustering coefficient of 2/15=0.13. The middle node in the right-hand network on the other hand, has as many as 8 of the 15 possible trials complete, meaning it has a clustering coefficient of 8/15=0.53.

One can also immediately see that the network on the right is much more cohesive than the one on the left. It is because of this that I propose to use the clustering coefficient to test Cross' (2013) theory on variable internal cohesiveness and epistemic community influence. It intuitively makes sense, while also allowing for easy measurement and comparison.

The clustering coefficient can either be calculated for individual nodes (local clustering coeffiecient) or for the entire network or a select subgroup of it (global clustering coefficient). They are formalized in the following equations:

Local clustering coefficient:

Equation 4. Local clustering coefficient

$$C_i = \frac{2|\{e_{jk} : v_j, v_k \in N_i, e_{jk} \in E\}|}{k_i(k_i - 1)}.$$

Global clustering coefficient:

Equation 5. global clustering coefficient

$$\bar{C} = \frac{1}{n}\sum_{i=1}^{n} C_i$$

By comparing the clustering coefficient of the ACIA researchers with the general scientific network, as well as performing a statistical significance test, one can thus surmise if the influential ACIA researchers really were more cohesive or not, compared to the overall population.

5-2 Permutation tests

Performing a statistical significance test on network data is unfortunately not as straightforward as implied in the previous subheading. Most of modern statistics rest upon two major assumptions:

1. That the observations are *independent* from each other.
2. That they are drawn randomly from a *normally* distributed sample.

Neither of these assumptions hold true when it comes to network data. On the contrary, networks are per definition *inter*dependent, and they often display non-normal distributions, such as power law distributions.

Permutation testing is one way to overcome this problem. Permutation tests are non-parametric tests, like bootstrapping, in which the data is rearranged to create a new probability distribution. In a network context, this entails retaining the structure but randomly reassigning the position of nodes within that structure.

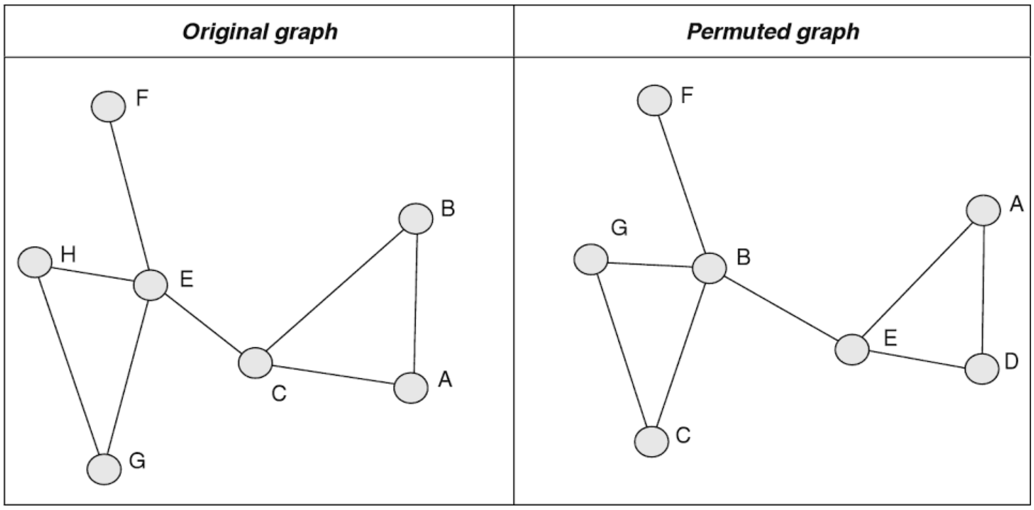

Figure 10. Example of a permuted graph © Christina Prell, Department of Sociology, University of Maryland

Figure 10 exemplifies this. In the original graph (left side), one will calculate the measurement one is interested in (in our case, the clustering coefficient), and then permutate that dataset (the right hand side is an example of one iteration of the permutation). This procedure is done tens of thousands of times. In every iteration, the clustering coefficient is recalculated and compared to the original graph. If the results from these permutations are similar, one can assume the original result was mostly due to chance. However, if the original score happens only with extreme rarity, then one can feel increasingly confident that the findings are statistically significant. (Prell 2012, p. 205).

The statistical significance test chosen is the tried and true Pearson's product-moment correlation. The dependent variable is the aforementioned clustering coefficient, a continuous variable (ranging from 0 to 1), while the independent variable is a binary, nominal encoding of ACIA coauthorship (authors= 1, non-authors=0). The permuted Pearson’s correlation were also calculated for all the aforementioned centrality measurements (degree, closeness, and betweenness) in order to explore other potential hypothesis.

This permutated correlation analysis is a very simple and rather crude method for inference testing in a network analysis. Recent developments of more advanced models of inference testing, such as Exponential Random Graph Models (ERGM) would have been preferable. However, since this thesis is the first application of SNA inference testing in the field of epistemic community research known to the author, it was considered more prudent to rely on simple, proven techniques, rather than highly advanced procedures that are still in development.

5-3 Graph simplification

As mentioned earlier, the graph was assembled in a tripartite structure. This is a convenient way to keep the different nodes separated in a clean and orderly way. However, it is not appropriate when we want to study the relationship between the same kinds of nodes, e.g. scientist directly to another scientist. Additionally, none of the social network analysis measures we have seen so far were designed to work on multilevel graphs, and will therefore not yield meaningful answers.

For the purposes of answering the research question, it is therefore necessary to construct a simpler graph from the main tripartite graph. This is done through a method called projection, in which indirect links are replaced with direct links, and the unused nodes are subsequently removed from the graph. In order to study the cohesion amongst the scientists who authored the Arctic Climate Impact Assessment report, it was necessary create direct links between them based on their co-authorship patterns. Additionally, since the main interest of this study is the ACIA scientists, it makes sense to get rid of everything earlier than a decade before the reports 2005 release.

The projection algorithms were implemented using the *igraph* package (Csardi, G., & Nepusz, T. 2006) available for the R programming language (Team, R. Core. 2000). This package, in addition to *tnet* by Opsahl (2012), and the visualization program *Gephi* (Bastian, M., Heymann, S., & Jacomy, M. 2009) were the software used for all prior and subsequent network analyses.

The finished graph appropriate for this study were thus a single-layered, undirected, weighted graph containing only the researchers who had published Arctic research in the period of 1995-2005.

V Analysis

1 The research network

Figure 11 sees the visualization of the 1995-2005 international Arctic research community. Scientists with similar colours generally belong to similar research communities, conducting science on related topics. Node size is determined by the degree centrality of the scientist in question (i.e.: scientists who collaborates with many people will seem more prominent in the graph).

Every link between nodes signifies a co-publication. The opacity of the links decreases with increased link weight (i.e.: the more often two scientists collaborates, the darker the lines will be).

The red nodes are the scientists who wrote the Arctic Climate Impact Assessment report. A red line indicates two members of ACIA having collaborated on one or more publications other than the ACIA report.

Immediately, we can see some interesting patterns emerge. While there definitely is a core of seemingly very cohesive ACIA members forming in the middle of the network, they are also noticeably spread out. Almost every part of the network sees at least one ACIA (red) member. It is therefore hard to tell with the naked eye if the ACIA participants are more or less cohesive than the rest of the network generally.

The big green and red group in the middle are mostly earth system scientists, oceanologists, or researchers studying the global atmosphere. They are in other words the “pure” climate change scientists, and it makes sense that they occupy a large central part of the network.

Above them and to the left are scientists studying various species, starting with fish and ending up with microbes at the very top of the graph. Left from the core you find scientist studying mammals, reindeer, seals, and to the far left-hand side, sociologists, anthropologist, and public health experts researching local populations and indigenous communities.

Down and to the right of the core is where geologists, hydrologists, and glaciologist are to be found. While the right-hand side of the graph are occupied by chemists, physicists, and other “pure” natural science experts. Figure 11 shows how smaller epistemic communities are embedded within the larger Arctic research community, exemplifying how social network analysis can be used to analyse “networks within networks” (Della & Mosca, 2005).

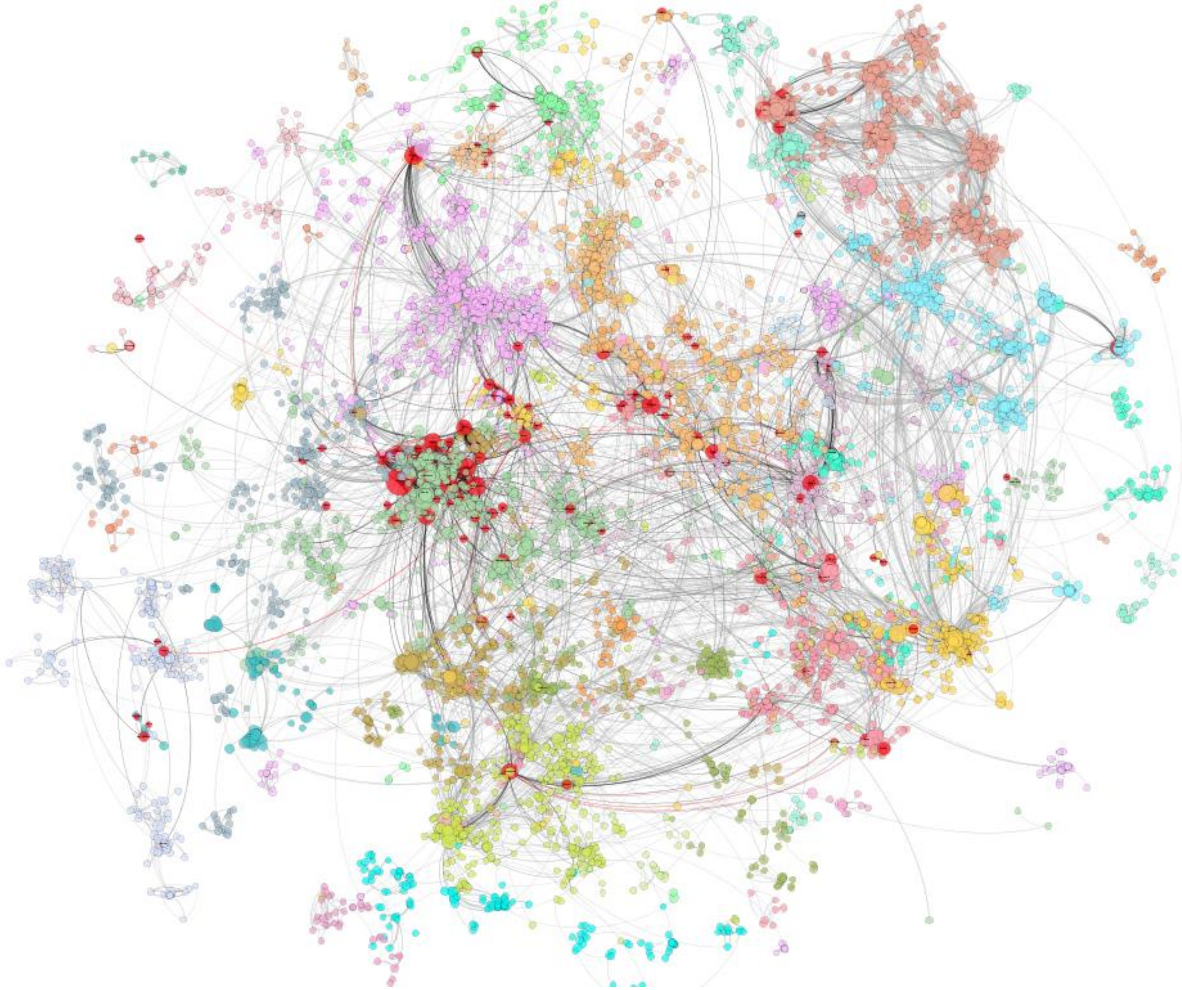

Figure 11. The ACIA network

2 *Results of the permutation tests*

After running the permutation for 10,000 iterations, we get the results in Table 3. Results of permutation testI ran a simple correlation test between a binary 1/0 acia variable (whether the scientist was part of ACIA or not) with the three centralities and of course the clustering coefficient.

All four network measures were found to have statistically significant correlations after the permutation tests (p-value <0.005), but varied greatly in the strength of the correlation, indicating that the ACIA authors had decidedly non-random, but not necessarily strong, deviations from the other researchers in the network.

Recall the research question: "*is the cohesion, as measured by the clustering coefficient of their collaboration pattern, of the ACIA epistemic community higher than that of the general research network?*" We are now in a position to answer this question. If the correlation of clustering coefficient is high and statistically significant, the answer to the research question is positive, adding support to Cross' (2013) hypothesis.

Immediately we notice that clustering coefficient is actually *negatively* correlated with ACIA membership. The strength of the permuted Pearson's correlation is a negative 0.27. This means that the ACIA members, all things being equal, are actually embedded in *less* cohesive groups, contrary to Cross' original hypothesis.

Examining the various centrality measurements, we see that ACIA membership is positively correlated with degree centrality, meaning that ACIA members generally have more coauthorship relationships than the general population.

There is a very small positive correlation with closeness centrality, implying that ACIA members are little closer to the centre of the network than the average scientist, but not much.

The correlation with betweenness centrality is particularly high. Keep in mind that all of these measurements max out at 1, so a 0.2 increase in the correlation of the betweenness centrality is quite strong.

VECTOR PERMUTATION TEST:

(NUMBER OF ITERATIONS = 10000)		
ACIA	correlation	p-value
DEGREE CENT	0.1306728	0.00000000000000022
CLOSENESS CENT	0.04353862	0.00004004
BETWEENNESS CENT	0.20009739	0.00000000000000022
CLUST COEFF	-0.02777781	0.0000000000006899

Table 3. Results of permutation test

3 Discussion

3-1 Clustering Coefficient

As mentioned, the clustering coefficient of the ACIA community's collaboration pattern is lower than that of the general research network, implying that in the case of the Arctic Climate Impact Assessment Report, the epistemic community were not only *not* particularly cohesive, it was actually significantly less cohesive (when operationalized as the clustering coefficient in a co-authorship network) than the rest of the network. The answer to the research question is therefore a straightforward "no." This is the opposite of the original hypothesis stipulated in introductory part of this thesis, as well as Cross' (2013) theory.

The following parts of the thesis will seek to outline a potential alternative structural theory for epistemic influence, which could be the subject of future research.

3-2 Alternative hypothesis

That the positive correlation with the betweenness centrality was so strong was very surprising. Especially in conjunction with the unexpected finding that the clustering coefficient was negatively correlated with being an ACIA member. This seems to imply that the strength of the ACIA group lay not in their cohesiveness, but in their ability to reach across disciplinary divides.

Recall from Chapter IV that betweenness centrality is "the number of times a node acts as a bridge along the shortest path between two other nodes." Essentially a node that serves to bridge disparate communities. Moreover, recall from Figure 11. The ACIA network how ACIA members were distributed widely throughout the network. Looking at it again, it seems the influence of the ACIA report was not a result of one very cohesive group of researchers, but a loose-knit community of researchers consisting of highly influential scientists in a diverse set of scientific disciplines.

One is reminded of one of the classic articles of network science, and one of the most highly cited articles in all of social science (Green 2016), Mark Granovetter's The Strength of Weak Ties (1973, 1983). In those articles, he argues that highly cohesive cliques in a network, especially one with many closed triangles, tend to create redundancies in terms of information flow, as your tight-knit friends are likely to share the same knowledge as you, and new information is less likely to enter the group. His empirical foundation was based on interviews he had done with job seekers who had recently acquired a job through personal contacts. It turned out more than 80% of them had gotten the job through a contact that he saw only occasionally or rarely (i.e.: a weak tie), while those who acquired a job through their close friends were in short supply. He concluded that weak ties are the most valuable for diffusion across a network because they create shortcuts across dense cliques (Granovetter 1973, 1983).

I am not arguing that the ACIA network serves as an efficient vehicle for the rapid transmission of knowledge. -A co-authorship network would not be a very efficient vehicle for any kind of diffusion. However, there might be other insights to be gained from the strength of weak ties concept. As we have touched upon earlier, the ACIA report displayed a remarkable diversity amongst its authors. This diversity is reflected in the high betweenness centrality of the members, as they represent a broad set of different disciplines and epistemological traditions, some of which are rarely associated with climate science. A small, insular group is easier to dismiss, no matter how cohesive, than a broad alliance including very disparate social groups.

One potential causal factor in this the way theory convergence can serve to undermine uncertainty in a social system (Barrett & Dannenberg 2014)

VI Limitations

1. Graph structure

One major problem unaddressed thus far in this study is the fact that collaboration patters differ wildly between disciplines. In disciplines like environmental sciences, atmospheric sciences, and marine biology often see up to eight authors per publication. While in the social sciences two and three co-authors seems to be average. These varying patterns of scientific collaboration can have a strong effect on the network structure. This seems to have manifested itself in the network, where the natural sciences have created more dense subgroups than did other disciplines. However, the choice of case study, the ACIA authors, seems to have counteracted some of this, as it was such a diverse group. Yet it is still an issue.

2. Limited scope

Another issue with the case selection is that it is hard to generalize from just one case. A large-N comparative study of the clustering coefficient of several influential research communities across time and scientific disciplines would shed much light on the role played by the structure of collaboration patterns on epistemic community influence.

3. Data integrity

As we remember from Table 2 on page 25, the dataset was very messy in its raw form. Imperfect data is an unpleasant fact when performing big data analyses like this, and I feel I managed to take care of most of the problems by employing all the cluster techniques mentioned in Chapter IV, but there is no way to be sure.

4. Only one mode of collaboration captured

The network created for this study relies only on links created by coauthorship. That misses many other modes scientists collaborate and strengthen cohesion over, such as attending conferences together, working at the same institute, working together in government or the private sector, reading each other's manuscripts, emailing and so on. All of these patterns of collaboration would have been useful for this study.

5. Strong assumptions underlie the research

As mentioned in the Case selection: The Arctic Climate Impact Assessment Report part, this study does not engage with the fundamental question of whether or not the ACIA members was a valid example of an influential epistemic community. A lack of disagreement in the literature does not necessarily mean there is no room for doubt per se.

A more looming group of assumptions are those that come with the epistemic community framework. As a part of the constructivist turn, the epicoms framework depends on a set of assumptions that are ardently contested by other branches of IR theory. These include for example that state preferences are not fixed, but can be changed; policy-makers are not fully rational, and can make mistakes; "*states are functionally differentiated, they vary widely according to their state–society relations and the technical capacity of the state to formulate and enforce public policies*" (Haas 2016).

VII Conclusion

1. Summary

This analysis operationalized and tested a theory of epistemic community influence. The theory argues that cohesion is a critical component in a community's ability to succeed. I defined "cohesion" as a high clustering coefficient in a coauthorship network and applied it on a network of Arctic researchers, particularly the group of researchers who collaborated on the influential Arctic Climate Impact Assessment report (ACIA 2005).

The results challenged the original hypothesis and opened for a more complex understanding of the effect of internal cohesion on an epistemic community's political influence.

2. Future research

One obvious way to expand on the findings in this thesis is to bring in more than one case. Lists of epistemic communities who have failed or succeeded could easily be matched with the current database, laying the foundation for larger-N comparative research.

As one can see from Figure 11, the ACIA researchers are also part of other epistemic communities. These overlapping memberships could be analysed by taking advantage of developments in multilayer social network science (Dickison, M. E., Magnani, M., & Rossi, L. 2016).

Multilayer social networks could also be used to include other patterns of scientific collaboration, by for example datamining conference participation, and combining that with the current network.

The tools developed in Discursive Network Analysis (Leifeld, 2017) would go well with the dynamic capabilities in the current database.

The shape of the network bore resemblances to a core-periphery structure. That could serve to harmonize Cross' theories with my findings: a cohesive core that stands for much of the initial mobilization, but with "bridge" connections to allies that will give legitimacy to the movement.

VIII Acknowledgements

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